Optimization of Water Distribution Network Design Using Rafflesia Optimization Algorithm Based on Opposition-based Learning

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Abstract

About 70% of the total cost of the water distribution system is used in the design of water distribution network (WDN), and selecting the most suitable pipe diameter for the WDN is the main way to reduce construction costs. The Rafflesia optimization algorithm (ROA) is a novel meta-heuristic algorithm, which was proposed recently. It has the characteristics of escaping local optimal solutions and stable performance. To further increase the solution quality and convergence speed of the algorithm, the opposition-based learning strategy is adopted in this paper to initialize the ROA algorithm population (namely the OBLROA algorithm). In this paper, the two-loop pipe network is taken as an actual test case, and the OBLROA algorithm is used to design the minimum cost pipe diameter combination. The experimental results show that the OBLROA algorithm can find the lowest cost pipe diameter combination of the two-loop pipe network under the constraints of pressure and velocity. Compared with some previous research work, the OBLROA algorithm needs the least number of evaluations to find the optimal solution, showing strong competitiveness.

Keywords: Water distribution network, Rafflesia optimization algorithm, Opposition-based learning, Two-loop network

1 Introduction

The water distribution network (WDN) is one of the important infrastructures in urban life, providing basic services such as clean drinking water and fire-fighting water to urban residents [1-2]. Pipe diameter selection is critical to the operational efficiency, cost and reliability of water distribution systems. The pipe diameter selection of the WDN has been proved be an NP-hard combinational optimization problem [3-4]. Early pipe diameter design methods usually use traditional methods [5-6]. However, these methods cannot fully take into account the influence of various complex factors of the entire pipe network, so the optimal pipe diameter selection cannot be obtained. With the development and popularization of optimization algorithms [7-8], more and more people begin to use optimization algorithms to solve NP-hard combinatorial optimization problems [9-11]. Therefore, some scholars try to use intelligent optimization algorithms to optimize pipe diameter design to reduce the cost of optimal design of the WDN [12-13].

The optimal design of the WDN commonly involves the use of optimization algorithms [14-15], common algorithms include genetic algorithm (GA) [16], differential evolution (DE) algorithm [17-18], particle swarm optimization (PSO) algorithm [19-20], etc. For example, Vairavamoorthy and Ali optimized the pipe diameter design of the Hanoi network and the New York City tunnel system using a real-number encoded GA algorithm [21]. By combining the DE algorithm with the hydraulic model solver EPANET, Vasan and Simonovic solved the design optimization problem of the WDN [22]. Surco et al. used the PSO algorithm to optimize the pipe diameter design of four WDNs, including two-loop network and Balerma network [23]. In addition, the simulated annealing algorithm (SA) [24-25], shuffled frog leaping algorithm (SFLA) [26-27], water cycle algorithm (WCA) [28-29], whale optimization algorithm (WOA) [30-31], etc. have also been used to optimize the design of the WDN. Although the above algorithms can be used in the optimal design of the WDN, there are some limitations associated with most algorithms [32-33], such as premature convergence [34], easy to fall into local optimal solution [35], etc. These shortcomings make them less efficient in solving problems, and cannot give the optimal solution in a short time.

Rafflesia optimization algorithm (ROA) algorithm is a newly developed intelligent optimization algorithm [36]. It keeps the exploitation process and the exploration process in balance. The algorithm still has the ability to escape the local optimal solution at the later stage of iteration. The population initialization of the ROA algorithm adopts a random method, and values are randomly selected in the feasible domain space. However, the random initialization of the population [37-38] may have some disadvantages, such as the relatively uneven distribution and the quality of the initial solution. These shortcomings will cause the algorithm to spend more time and resources to search for a better solution. Therefore, the opposition-based learning strategy [39-40] is adopted in this paper to initialize the population of the ROA algorithm to improve the quality of the initial population. And the ROA algorithm based on the opposition-based learning strategy

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(OBLROA) is employed for optimizing the pipe diameter selection of the WDN. The contributions of this paper are as follows:

1. Rafflesia optimization algorithm based on opposition-based learning (namely the OBLROA algorithm) is proposed.

2. The optimal design problem of the two-loop network is solved by the ROA and the OBLROA algorithm. This is also the first research on the application of the ROA algorithm to solve the WDN.

3. Compared with some previous research work, the OBLROA algorithm shows excellent performance in solving the design problem of the two-loop pipe network.

The remaining content of this paper: Section 2 introduces the optimal design model of the WDN and the original ROA algorithm. Section 3 describes the OBLROA algorithm, and gives the scheme for the algorithm to solve the optimal design of the WDN. The solving ability of the algorithm to the WDN design problem is tested by using a two-loop network model in Section 4. Section 5 summarizes the work of this paper.

2 Preliminaries

2.1 The Optimal Design of Water Distribution Network

The optimal design of the WDN can be stated as a minimum cost optimization problem with the choice of pipe size as the decision variable. The original objective function of the problem can be expressed as:

$$minZ\left(D\right) = \sum\nolimits_{i=1}^{N_{pipe}} c_i(D_i)L_i. \tag{1}$$

Where Z is the construction cost of the WDN. The total number of pipes is N_{pipe}. D_i represents the diameter of the i-th pipe. $c_i(D_i)$ is the unit price of the pipe with diameter D_i. L_i represents the length of the i-th pipe.

Assuming that the structure, node demand, node elevation and pipe length of the WDN are known, the following conditions need to be met to find the minimum cost combination of pipe diameters:

(1) Mass conservation constraints

This constraint requires that the total flows flowing into nodes in a pipe network is equal to the total flows flowing out of nodes.

$$\sum\nolimits_{j=1}^{N_{nodes}} Q_j = 0. \tag{2}$$

where N_{nodes} is the total count of nodes. Q_j represents the inflow or outflow traffic from the j-th node.

(2) Energy conservation constraints

Closed pipes form loops. This constraint requires that the algebraic sum of the head losses in the pipes in each loop be equal to zero. The energy equation of the p-th loop is expressed as:

$$\sum\nolimits_{i\in p} h_i = 0, \quad \forall p \in l,\ i \in N_{pipe}. \tag{3}$$

where h_i represents the head loss of the i-th pipe. l represents the total count of loops in the WDN. h_i is expressed by the Hazen-Williams equation as:

$$h_i = \frac{10.7 \cdot Q_i \cdot L_i}{C^{1.852} \cdot D_i^{4.87}}. \tag{4}$$

Where Q_i represents the flow in the i-th pipe. C is the roughness coefficient of the pipe material.

(3) Nodal pressure constraints

To meet the user's demand for water consumption, the node pressure of any node in the pipe network should meet or exceed the minimum service node pressure, namely:

$$H_j \geq H_{min}. \tag{5}$$

Where H_j represents the pressure of the j-th node. H_{min} represents the minimum service pressure.

(4) Standard pipe diameter constraint

$$D_i \in D = \{D_1, D_2,\ \dots, D_n\}. \tag{6}$$

D is a set of standard pipe diameter sizes available in the market.

(5) Pipe velocity constraints

When the velocity of water within a pipe is too high, it is easy to cause a pipe burst phenomenon. Therefore, it is necessary to constrain the water velocity within the pipe.

$$V_i \leq V_{max}. \tag{7}$$

Where V_i represents the velocity of water within the i-th pipe. V_{max} represents the maximum allowable water velocity.

To prevent the pipe from bursting, according to the pipe velocity constraints, a penalty item for violating constraints is incorporated into the original objective function. Mathematically, the updated objective function is:

$$\min Z(D) = \sum\nolimits_{i=1}^{N_{pipe}} c_i(D_i)L_i + \sum\nolimits_{i=1}^{N_{pipe}} \delta \cdot v_i(D_i). \tag{8}$$

The second term on the right-hand side of the equation represents the penalty term. δ is the penalty coefficient. $v_i(D_i)$ is a binary function with a value of 0 or 1.

$$v_i(D_i) = \begin{cases} 1, & V_i > V_{max} \\ 0, & V_i \leq V_{max} \end{cases}. \tag{9}$$

2.2 Rafflesia Optimization Algorithm

As a meta-heuristic algorithm, the ROA algorithm is developed according to the growth characteristics of Rafflesia plants [41-42]. It mainly contains three stages: the stage of attracting insects, the stage of "swallowing" insects, and the stage of dispersing seeds. In the stage of attracting insects, the ROA algorithm uses two different strategies to update individuals with poor fitness and good fitness respectively. In the stage of "swallowing" insects, by reducing the worst individual, the execution efficiency of the ROA algorithm is enhanced. In the stage of dispersing seeds, the ROA algorithm starts from the current optimal individual to find a better solution in the global scope.

2.2.1 The Stage of Attracting Insects

The stage of attracting insects uses two strategies to update individuals. Among them, strategy 1 updates individuals with poor fitness, and the number accounts for 1/3 of the population size. Strategy 2 updates individuals with good fitness, and the number accounts for 2/3 of the population size.

Strategy 1:

Strategy 1 uses new individuals to replace individuals with poor fitness in the population. The dimension k (k = 1, 2, …, D) of the newly added individual is abstracted into a 3D space, as shown in Figure 1. The equation used to calculate the position of the newly added individual is:

$$X_{i_k} = X_{best}^k + d \times \sin\beta^k \cos\gamma^k. \quad \textbf{(10)}$$

Where X_i (i = 1, 2, …, NP/3) is the new individual. X_{best} represents the current best individual. β_k represents the angle between $\overrightarrow{X_{best}X_i}$ and dimension k+1, and the value is (0, π/2). $\overrightarrow{X_{best}X_i}$ is a vector composed of X_i and X_{best} · γ_k represents the angle between the projection of $\overrightarrow{X_{best}X_i}$ on the plane formed by k-dimensional and (k+1)-dimensional and k-dimensional, and the value is (0, π). The distance between X_i and X_{best} is represented as d. Its value is equivalent to the distance between random individual X_R and X_{best}.

$$d = \sqrt{\sum_{k=1}^{D}(X_R^k - X_{best}^k)^2}. \quad \textbf{(11)}$$

Then, the new individuals will replace the individuals with poor fitness:

$$X_{worst}^i = X_i. \quad \textbf{(12)}$$

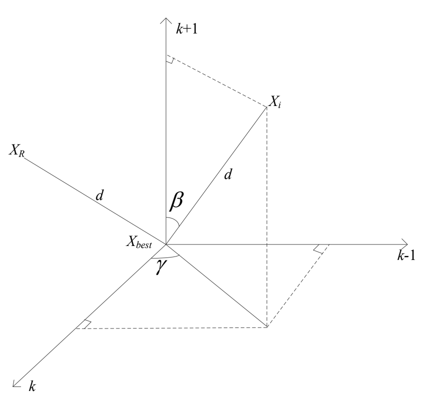

Figure 1. Schematic diagram of dimension representation

Strategy 2:

The position update equation of individuals with good fitness is:

$$X_j = X_j + \mu \times \vec{v} \times t + (X_{best} - X_j) \times (1-\mu) \times rand. \quad \textbf{(13)}$$

Where X_j (j = 1, 2, …, $\frac{2\times NP}{3}$) is the currently updated individual. μ represents an impact factor whose value is in the interval [-1,1]. $\vec{v}$ is the velocity of the individual, which is equal to the sum of the translational velocity $\vec{v_1}$ and the rotational velocity $\vec{v_2}$.

$$\vec{v_1} = \frac{\omega_0}{2}\sqrt{A^2\sin^2(\omega_0 t + \theta) + B^2\cos^2(\omega_1 t + \theta)}. \quad \textbf{(14)}$$

$$\vec{v_2} = \vec{v_2}\omega_0\cos(\omega_0 t + \theta + \varphi). \quad \textbf{(15)}$$

Where A is the amplitude of individual movement, and the value is 2.5. B is the lateral offset, the value is 0.1. ω_0 and ω_1 are the frequency period and the horizontal frequency period respectively, and the values are both 0.025. θ represents the phase whose value is in the interval (2, 2π). The phase difference between translation and rotation is represented by φ, and its value is -0.78545. The variable represents time, and its value is 1.

2.2.2 The Stage of “Swallowing” Insects

The ROA algorithm executes the stage of “swallowing” insects after a specific number of iterations. At this stage, the algorithm will eliminate the worst individual. During the entire iterative process of the algorithm, the number of individuals eliminated accounts for nearly one-third of the total population size.

2.2.3 The Stage of Dispersing Seeds

In this stage, the position update equation of the individual is:

$$X_m = X_{best} + rd \times \exp(\frac{iter}{Max\_iter} - 1) \times sign(rand - 0.5). \quad \textbf{(16)}$$

Where X_m (i = 1, 2, …, NP) is the position of the individual to be updated. $iter$ represents the current number of iterations, and Max_iter is the maximum number of iterations. $e^{\frac{iter}{Max\_iter}-1}$ is an impact factor that varies with the number of iterations. The value of $sign$ ($rand$ − 0.5) is 1 or -1, and its purpose is to increase the diversity of dimension values. rd is the distribution range of the individual.

$$rd = rand \times (ub - lb) + lb. \quad \textbf{(17)}$$

Where $rand$ represents a random number in the interval [0, 1]. ub and lb are the upper and lower bounds of the interval, respectively.

3 Rafflesia Optimization Algorithm Based on Opposition-based Learning Strategy

3.1 The Opposition-based Learning Strategy

The original ROA algorithm uses a purely random strategy to initialize the algorithm population, which may lead to a poor initial solution of the algorithm. The quality and convergence speed of the obtained optimal solution are also affected. The population initialization method using opposition-based learning can enhance the accuracy and effectiveness of the algorithm's initial solution. In addition, it can also broaden the search for feasible solutions. To improve both the quality of the initial solution and the optimal solution, and to speed up the convergence speed of the ROA algorithm, this section will implement the opposition-based learning approach for population initialization.

First, a random initial population of NP individuals is generated using a random strategy. Because the optimal design of the WDN is a discretization problem, each individual x in the population is generated by discretization.

$$x = round(lb + rand \times (ub - lb)). \quad \textbf{(18)}$$

After that, each individual in the random initial population generates its reverse individual x' according to the Equation (19).

$$x' = ub + lb - x. \quad \textbf{(19)}$$

Finally, the pipe diameters selected by all individuals in the random population and the reverse population are sequentially transferred to the hydraulic model for simulation calculation. Upon completion of the calculation, the cost values of 2*NP individuals are sorted in ascending order, and the first NP individuals with lower cost are selected as the final initial population. In the subsequent iterative process, the update strategy of the three phases of the OBLROA algorithm is consistent with the ROA algorithm.

3.2 Coding Scheme and Solution Steps

The OBLROA algorithm is a continuous optimization algorithm, and the optimal design of the WDN is a discrete optimization problem. Therefore, when using the OBLROA algorithm to find the optimal pipe diameter combination, it is necessary to carry out integer discretization of the OBLROA algorithm. This section designs the rounding rules in the iterative process of the algorithm. First, the correspondence between the WDN model and the OBLROA algorithm is established. The number of pipes in the WDN model corresponds to the number of dimensions of the algorithm. The position number of the optional pipe diameter in the collection corresponds to the dimension value of the population individual. The maximum position number is denoted as *NUM*. The dimension value of the population individual is a continuous variable after being updated in different stages of the OBLROA algorithm. After that, the continuous variables are discretized. The updated dimension values are taken as absolute values and rounded up. When the dimension value is greater than *NUM*, the remainder is allocated to the dimension value. When the dimension value is equal to 0, a random value is assigned to the optional position number. Finally, the diameter combination selected by the individual can be known according to the dimension value of this individual.

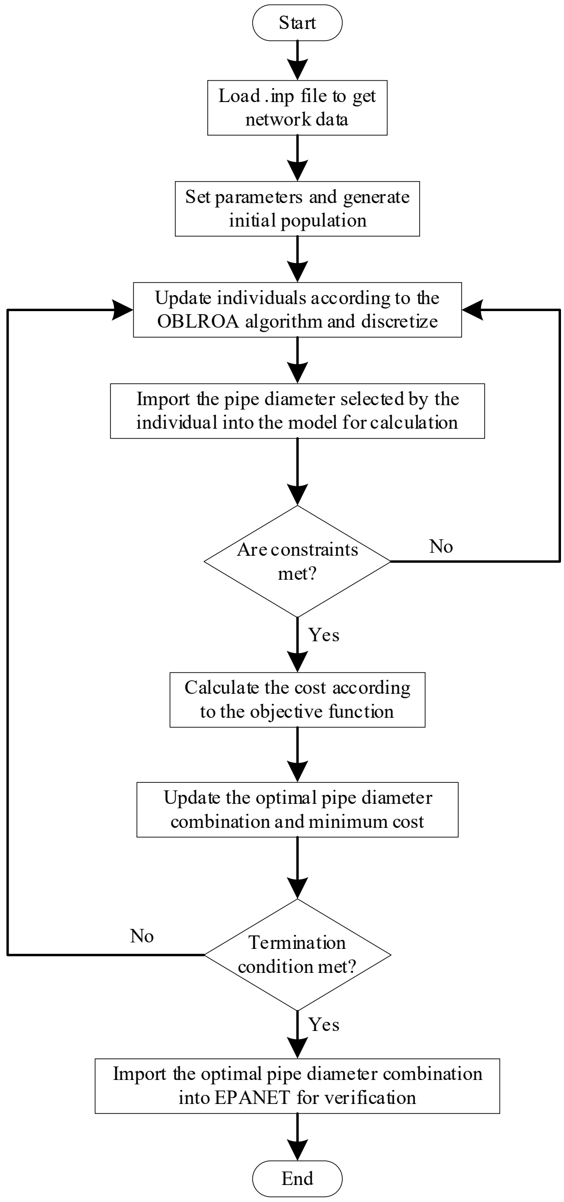

Figure 2. Flowchart of the OBLROA algorithm linked to the hydraulic simulation

Figure 2 depicts the flowchart of the OBLROA algorithm linked to the hydraulic simulation. The steps to solve the WDN optimal design using the OBLROA algorithm are as follows:

Step 1: Load the .inp file of EPANET to obtain data such as the number of pipes, pipe length, and number of nodes of the pipe network model;

Step 2: Set the experimental parameters and algorithm parameters, and generate the initial population based on the opposition-based learning strategy, and record the initial optimal cost and optimal pipe diameter combination;

Step 3: Update the population individual based on the different stages of the OBLROA algorithm, and round the dimension value of the population individual according to the above discretization rules;

Step 4: Transfer the pipe diameter selected by the population individual to EPANET for simulation calculation, and obtain data such as pipe flow velocity and node pressure;

Step 5: Judging whether the data obtained in Step 4 satisfies constraints such as node pressure and pipe velocity. If the conditions are met, calculate the cost value according to the objective function; otherwise, go to Step3;

Step 6: Update the current optimal cost and optimal pipe diameter combination. Check if the termination condition has been satisfied. If yes, transfer the optimal pipe diameter combination to EPANET for verification and rationality check; otherwise, go to Step 3.

4 Experimental Simulation and Analysis

The hydraulic model of the two-loop network is used to evaluate the effectiveness of the OBLROA algorithm in solving the design problem of the WDN in this section. As shown in Figure 3, the two-loop network has 7 nodes and 8 pipes, and has a 210-meter reservoir for its water supply. All pipes are 1000 meters in length. The basic information of each node is listed in Table 1. The roughness coefficient C of all pipes is 130, the maximum allowable flow velocity V_{max} is 3m/s, and the minimum allowable pressure head H_{min} of all nodes is 30m. The available pipe diameters and corresponding construction costs of the two-loop network are shown in Table 2. There are 148 optional solutions for this pipe network, and the cost value of the known optimal solution is \$419000. The experiment sets the initial population size NP to 50, the maximum number of iterations Max_iter to 150, and the penalty coefficient δ to 100,000. The simulation test software is MATLAB2018b and EPANET2.2.

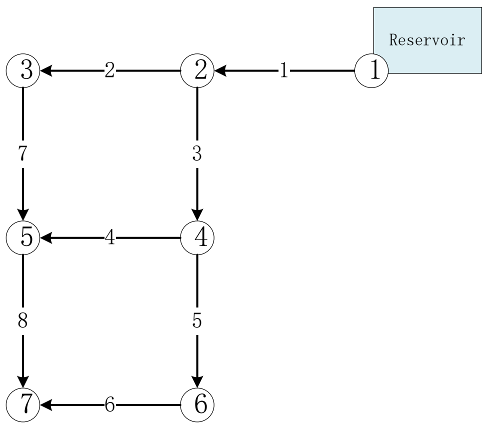

Figure 3. Layout of the two-loop network

Table 1. Basic data of the two-loop network

Node ID	Elevation (m)	Base demand (CMH)
Junc 2	150	100
Junc 3	160	100
Junc 4	155	120
Junc 5	150	270
Junc 6	165	330
Junc 7	160	200
Resvr 1	210	-

Table 2. Cost data for the two-loop network

Serial number	Diameter (in.)	Diameter (mm)	Cost (\$/m)
1	1	25.4	2
2	2	50.8	5
3	3	76.2	8
4	4	101.6	11
5	6	152.4	16
6	8	203.2	23
7	10	254.0	32
8	12	304.8	50
9	14	355.6	60
10	16	406.4	90
11	18	457.2	130
12	20	508.0	170
13	22	558.8	300
14	24	609.6	550

Table 3 records some previous research work and the solution results achieved via the original ROA algorithm and the OBLROA algorithm for the two-loop network design problem. The last column in the table records the minimum number of evaluations required by the algorithm to find the optimal solution. As shown in the table, the minimum number of evaluations required by Suribabu (2010) to obtain the optimal solution is less than the original ROA algorithm. However, with the addition of the opposition-based learning strategy to the ROA algorithm, a set of feasible initial solutions can be found more quickly. Therefore, the OBLROA algorithm required the least number of evaluations to find the optimal solution among all the research work in the table.

Table 3. Comparison with previous research work on the two-loop network

Author	Algorithm	Cost (\$)	Minimum evaluations
Savic and Walters (1997) [16]	GA	419,000	65,000
Cunha and Sousa (1999) [25]	SA	419,000	25,000
Eusuff and Lansey (2003) [26]	SFLA	419,000	11155
Suribabu and Neelakantan (2006) [20]	PSO	419,000	1875
Suribabu (2010) [17]	DE	419,000	1320
Sedki and Ouazar (2012) [18]	PSO-DE	419,000	2500
Reca, Martinez, and Lopez (2017) [43]	B-GA	419,000	2,000
Praneeth, Vasan, and Raju (2019) [29]	WCA	419,000	2,200
This work	ROA	419,000	1707
This work	OBLROA	419,000	939

Figure 4 depicts the convergence curves of the original ROA algorithm and the OBLROA algorithm in the process of solving the problem. The initial cost of the original ROA algorithm is $896,000. The minimum cost is 419000 when iterating to the iteration 35. In iterations 1 to 6, the algorithm evaluates 6*50 times. In iterations 7 to 21, the algorithm evaluates 15*49 times. In iterations 22 to 35, the algorithm evaluates 14*48 times. Therefore, the original ROA algorithm finds the optimal solution after about 1707 evaluations. The initial cost of the OBLROA algorithm is $763,000. When iterating to the iteration 17, the minimum cost is $419000. The OBLROA algorithm finds the optimal solution after about 939 evaluations (including 100 initialization evaluations).

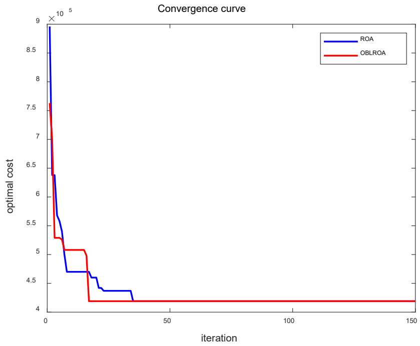

Figure 4. The convergence curves of the algorithms

Finally, the optimal pipe diameter combination obtained by the OBLROA algorithm is transferred to EPANET for verification. The verified nodal heads and pressures are recorded in Table 4. Data such as water flow velocity and head loss in the pipe are recorded in Table 5. Figure 5 depicts the schematic diagram of the nodal pressure in EPANET and the water velocities in the pipes. Pressure (Velocity) is a state parameter describing the nodes (pipes) in Figure 5. The redder the color of the node (line), the greater the pressure (velocity) of the node (pipe). In Figure 5, the value next to each node (line) is the pressure (velocity) value of the current node (pipe). It can be seen from the data in the chart that the verification results obtained by the hydraulic simulation calculation can meet the constraints in Section 2. This proves that the OBLROA algorithm can effectively and quickly solve the optimal design of the WDN.

Table 4. Data values at the nodes

Node ID	Head (m)	Pressure (m)
Junc 2	203.25	53.25
Junc 3	190.46	30.46
Junc 4	198.45	43.45
Junc 5	183.81	33.81
Junc 6	195.44	30.44
Junc 7	190.55	30.55
Resvr 1	210.00	0.00

Table 5. Data values in the pipes

Link ID	Flow (CMH)	Velocity (m/s)	Unit Headloss (m/km)	Friction Factor
Pipe 1	1120.0	1.90	6.75	0.017
Pipe 2	336.86	1.85	12.78	0.019
Pipe 3	683.14	1.46	4.80	0.018
Pipe 4	32.56	1.12	14.64	0.023
Pipe 5	530.58	1.14	3.00	0.019
Pipe 6	200.58	1.10	4.89	0.020
Pipe 7	236.86	1.30	6.66	0.020
Pipe 8	-0.58	0.32	6.75	0.034

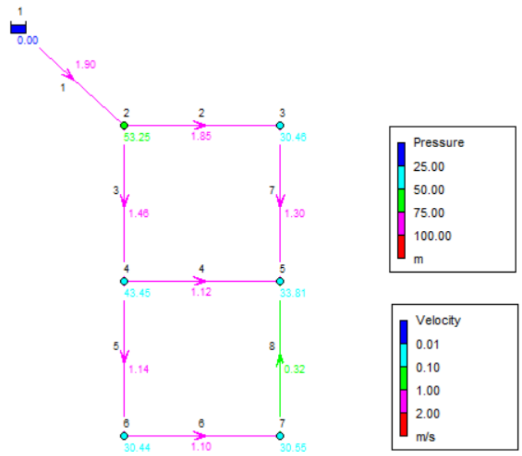

Figure 5. Schematic diagram of the two-loop network verification in the EPANET

5 Conclusion

This paper employs the ROA algorithm, which is based on the opposition-based learning strategy, to solve the optimal design problem of the WDN. By applying the opposition-based learning strategy during the initialization phase, feasible solutions to the problem can be quickly found, resulting in faster convergence of the algorithm towards finding the optimal solution. To successfully solve the optimal design problem of the WDN, this paper designs the discretization rules and solution steps of the OBLROA algorithm. In the experimental part, this paper uses the OBLROA algorithm to solve the hydraulic model of the two-loop network. Compared with the original ROA algorithm and some previous research works, the OBLROA algorithm requires the least number of evaluations to find the optimal solution. The verification results of the solution in EPANET further demonstrate that the OBLROA algorithm is highly effective in solving the optimal design problem of the WDN.

As a typical practical application, the WDN will always be the research focus of our work. In future work, we will continue to focus on how to further improve the solution performance of the ROA algorithm, and how to apply the algorithm to solve optimization problems in the WDN and other applications.

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